Assessment of Genetic Algorithm Selection, Crossover and Mutation Techniques in Reactive Power Optimization

Muhammad Tami Al-Hajri, MSEE
Power Distribution Department, Saudi Aramco
e-mail: mohammad.hajri.50@aramco.com
P. O. Box 6368, Dhahran 31311
East Province, Saudi Arabia

M. A. Abido, PhD
Electrical Engineering Department
King Fahad University of Petroleum & Minerals
e-mail: mabido@kfupm.edu.sa
Dhahran 31261, Saudi Arabia

Abstract: **In this paper assessment of different Genetic Algorithm (GA) selection, crossover and mutation techniques in term of convergence to the optimal solution for single objective reactive power optimization problem is presented and investigated. The problem is formulated as a nonlinear optimization problem with equality and inequality constraints. Also, in this paper a simple cost appraisal for the potential annual cost saving of these GA techniques due to reactive power optimization will be conducted. Wale & Hale 6 bus system was used in this paper study.**

I. INTRODUCTION

In the past two decades, the problem of reactive power optimization for improving the economy of power system operation has received a lot of attention especially after the latest famous blackout incident in worldwide major electrical system grids (New York, USA Grid) Reactive power optimization can be achieved by adjusting the power transformers taps, generator voltage and introducing switchable VAR sources to the system. In addition, the system losses can be minimized via redistribution of the reactive power in the system. This redistribution is subject to a number of constrains such as limits of generator bus voltage, tap settings of transformer limitations, availability of reactive power by the VAR sources [1,2].

Several optimization techniques to solve the optimal reactive power problem have been proposed in the literatures such as Sensitivity Analysis and Gradient-Based Optimization Algorithm, Non-Liner Programming (NLP) and the Heuristic Method to search for the Optimal Solution in the Problem Space. The first two techniques have many drawbacks, such as insecure convergence, long execution time and algorithmic complexity. The last technique has been theoretically proved that it does converge to the optimal solution with high probability.

Genetic Algorithm (GA) has been gradually introduced as powerful tools to hand complex, single and multi-nodal optimization problem. Like nature does to its living things, GA tends to develop a group of initial poorly generated solution via selection, crossover and mutation techniques to a set of acceptable solutions through successive generation. In the course of genetic evolution, more fit specimens are given greater opportunities to reproduce; this selection pressure is counterbalanced by mutation and crossover operation. The major advantage of GA lies in their computation simplicity, powerful search ability to reach the global optimum and been extremely robust with respect to the complexity of the problem.

This paper assess GA different selection, crossover and mutation techniques to solve optimal reactive power dispatch by controlling the value of shunt capacitors, generator voltages and transformer tap settings of a given system. GA was developed using object-oriented MATLAB programming which is used together with Load Flow MATLAB program in the optimization of the reactive power. Wale & Hale 6 bus system showing in Figure 1 was used in this study to demonstrate the potential of GA various selection, crossover and mutation techniques in reaching the optimal reactive power dispatch [1, 2, 3].

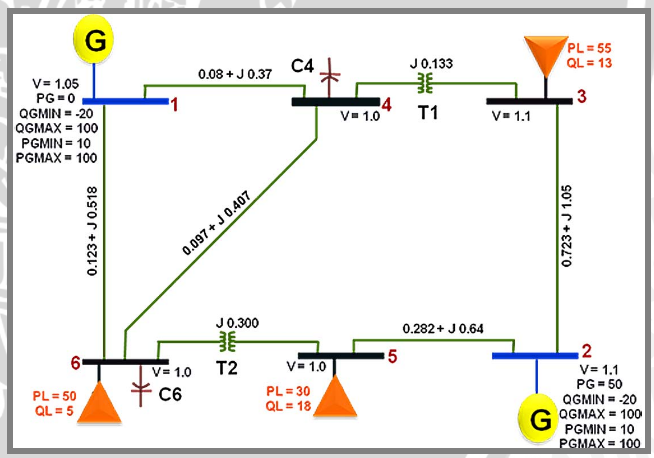

Fig 1: Wale & Hale 6 bus system

II. PROBLEM FORMULATION

The reactive power optimization problem is to optimize the steady state performance of a power system in terms of one or more objective function (in this paper one objective) while satisfying several equality and inequality constrains. Generally the problem can be formulated as follows;

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A. Objective Function

The objective is to minimize the real power loss (P_L) in the distribution lines that can be expressed as

$$J = P_L = \sum_{k=1}^{nl} gk\,[\,V_i^2 + V_j^2 - 2\,V_i\,V_j \cos(\delta_i - \delta_j)] \qquad (1)$$

Where **nl** is the number of distribution lines; **gk** is the conductance of the **k**[th] line, **Vi** $\underline{|\delta_i}$ and **Vj** $\underline{|\delta_j}$ are the voltage at end buses **i** and **j** of the **k**[th] line respectively.

B. Equality Constrains

These constrains represent load flow equations as

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j\,[G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)\,] = 0 \qquad (2)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j\,[G_{ij} \sin(\delta_i - \delta_j) + B_{ij} \cos(\delta_i - \delta_j)\,] = 0 \qquad (3)$$

Where i = 1,2,…,NB;NB is the number of buses; P_G and Q_G are the generator real and reactive power respectively; P_D and Q_D are the load real and reactive power respectively; G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and bus j respectively.

C. Inequality Constrains

These constrains represent the system operating constrains such as generator voltage V_G; generator reactive power outputs Q_G; transformer tap T; switchable VAR compensations QC and load bus voltage V_L

$$V^{min}_{Gi} \le V_{Gi} \le V^{max}_{Gi} \quad , i= 1,\ldots..,NG \qquad (4)$$

where $1.0 \le V_{G1} \le 1.15$ for Generator#1 (V_{G1})
$1.0 \le V_{G2} \le 1.1$ for Generator#2 (V_{G2})

$$Q^{min}_{Gi} \le Q_{Gi} \le Q^{max}_{Gi} \quad , i= 1,\ldots..,NG \qquad (5)$$

See Figure 1 for Generator Reactive Power Limitation

$$T^{min}_{i} \le T_i \le T^{max}_{i} \quad , i= 1,\ldots..,NT \qquad (6)$$

where $0.9 \le T_i \le 1.0$ for Transformer Tap (T_1 & T_2)

$$Q^{min}_{Ci} \le Q_{Ci} \le Q^{max}_{Ci} \quad , i= 1,\ldots..,NC \qquad (7)$$

where $0.05 \le Q_{Gi} \le 0.055$ for Capacitor (C_4 & C_6)

$$V^{min}_{Li} \le V_{Li} \le V^{max}_{Li} \quad , i= 1,\ldots..,NL \qquad (8)$$

where $0.9 \le V_{Li} \le 1.05$ for all Load Buses

Where NG, NT and NC are the number of generators, transformers and switchable VAR sources respectively.

Combining the objective and constrains, the problem can be mathematically formulated as a nonlinear constrained single

objective optimization problem as follows;

Minimize [$\mathbf{P_L}$] (9)
Subject to:
g(x,u) = 0 (10)
h(x,u) ≤ 0 (11)

where:

x: is the vector of dependent variables consisting of load bus voltage V_L, generator reactive power outputs Q_G. Hence, x can be expressed as

$$x^T = [V_{L1} .. V_{LNL}, Q_{Gi} \ldots Q_{GNG}] \qquad (12)$$

u: is the vector of control variables consisting of generator voltages V_G, transformer tap settings T, and shunt VAR compensation Qc. Hence, u can be expressed as

$$u^T = [V_{G1} .. V_{GNL}, T_1 \ldots T_{NT}, Q_{Ci} \ldots Q_{CNC}] \qquad (13)$$

g: is the equality constrains.
h: is the inequality constrains [3].

III. THE PROPOSED APPROACH

GA has the following advantages over other traditional optimization techniques;

- GA works on both a coding of the parameters to be optimized or the parameters themselves.
- GA searches the problem space using a population of trials representing solutions to the problem, not a single point, i.e. GA has implicit parallelism. This property ensures GA to be less vulnerable to getting trapped in local minima.
- GA uses an objective function assessment to guide the search in the problem space.
- GA uses probabilistic rules to make the decision.
- Can be used with non-continuous objective function.
- Does not require a lot of information about the optimized problem.

The mechanism of the proposed GA technique for reactive power optimization can be summarized in the following steps;

1) Generate an initial population of chromosomes; each chromosome consists of genes and each of these genes represents either transformer tap (T) settings or shunt capacitor (C) value or generator voltage (Vg). So, the

structure of each chromosome can be represented as $[T_1\ T_2\ C_4\ C_6\ Vg_1\ Vg_2]$.

2) Assign Fitness to each chromosomes as follows;
   a. Use the Newton-Raphson method to calculate the real power losses for each chromosome. The equality constraints are handled here.
   b. Identify if the identified inequality constraints in equations 4 to 8 are satisfied.
   c. Assign Fitness value to the Chromosomes that meet the voltage constrains (Fitness value = Real power losses).
   d. Assign Penalty value to those chromosomes who did not meet the voltage constrains (Penalty = 5).
   e. Assign Fitness value to the chromosomes that did not meet the voltage constrains (Fitness Value = Real power losses + Penalty).

3) Identify the Best Chromosome hat has the minimum Fitness value (Our optimization problem is a minimization problem) and store it (CR_Best).

4) Identify the Chromosomes parents that will go to the mating pole for producing the next generation, two methods were used for the parents selection
   a. The Tournament Selection Method.
   b. The Random Selection Method.

5) Perform genes Crossover for the meeting pool parents; three crossover methods were implemented;
   a. BLX Crossover Method.
   b. Flat Crossover Method.
   c. Simple Crossover Method.

6) Perform genes Mutation for the meeting pool parents after been crossovered; two Mutation methods were implemented;
   a. Random Mutation.
   b. Non-Uniform Mutation Method.

7) Go to Step#2 and repeat the above steps with the new chromosomes Generation generated from the original chromosomes parents after being crossovered and mutated.

8) In each time identify the best chromosome and compare its fitness with the stored one, if it is better (less real power loss) replace the best chromosome with this new one.

9) The loop of generation is repeated until the best chromosome in term of minimum real power loss is identified.

Figure 2 summarizes the aforementioned steps. Moreover, more detail about these steps will be given below [5, 6].

IV. GA SELECTION, CROSSOVER AND MUTATION DIFFERENT PROPOSED TECHNIQUES

A. SELECTION TECHNIQUES

In this section two GA selection mechanisms will be presented [4,7].

a. Tournament Selection Technique

The tournament selection technique does compare three chromosomes each time and allow the one with strongest fitness value (less real power loss RPL) to copy itelf twice in the meeting pool and the second one with respect to fitness value to copy itself only once in the meeting pool. The following figure (Fig.3) will demonstrate the Tournament Selection method.

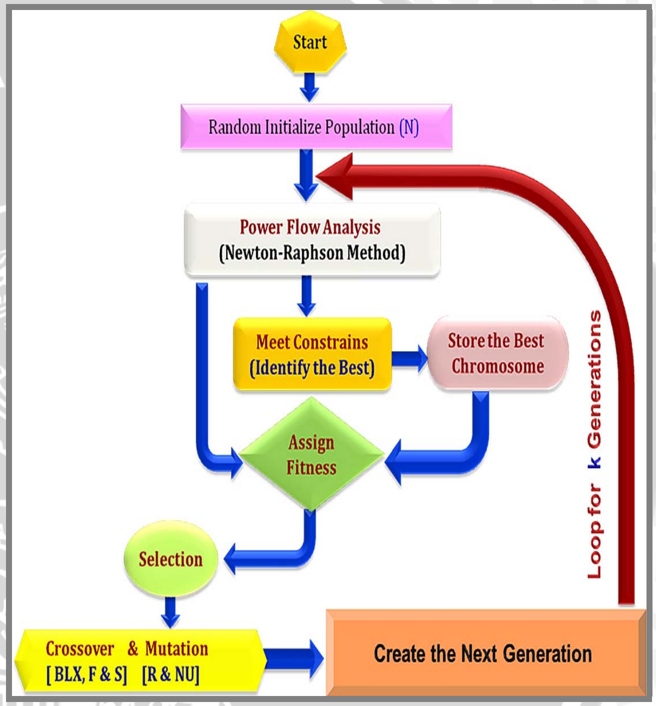

Fig 2: The GA Technique Mechanism Flow Chart

b. Random Selection Technique

The Random selection technique works by generating two random integer numbers (each represents a chromosome). Then these two randomly selected chromosomes fitness values are compared and the one with the better fitness value will go into the meeting pool. This randomly selected chromosomes mechanism will be repeated until the population in the meeting pool equals to the initial chromosomes population. Suppose that two chromosomes have been selected randomly (Chromososme#2 & Chromosome#7) as in Figure. 4, by comparing their fitness values (34 & 20) chromosome#7 will be nominated to go into the meeting pool.

B. CROSSOVER TECHNIQUES

Three GA crossover techniques will be explained in this section [4].

a. BLX Crossover Technique

By using the BLX crossover method an offspring is generated: $H = (h_1,\ldots.h_i,\ldots.h_n)$, where h_i is a randomly (Uniformly) chosen number of the interval $[C_{min}\text{-}I*\alpha, C_{max}+I*\alpha]$. $C_{max} = \max(C^1_i , C^2_i)$, $C_{min} = \min(C^1_i , C^2_i)$, $I = C_{max} - C_{min.}$ Figure 5 demonstrates the mechanism of the BLX crossover for the first genes ($T1_1$ & $T1_{2)}$ of the two chromosomes to be crossovered. In our BLX example $h1_1$ & $h1_2$ are chosen randomly from the interval (20 30).

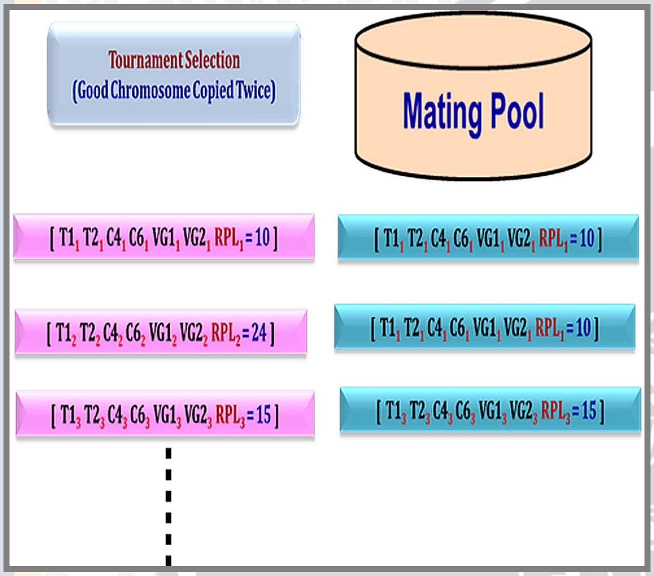

Fig 3: Tournament Selection Method Mechanism

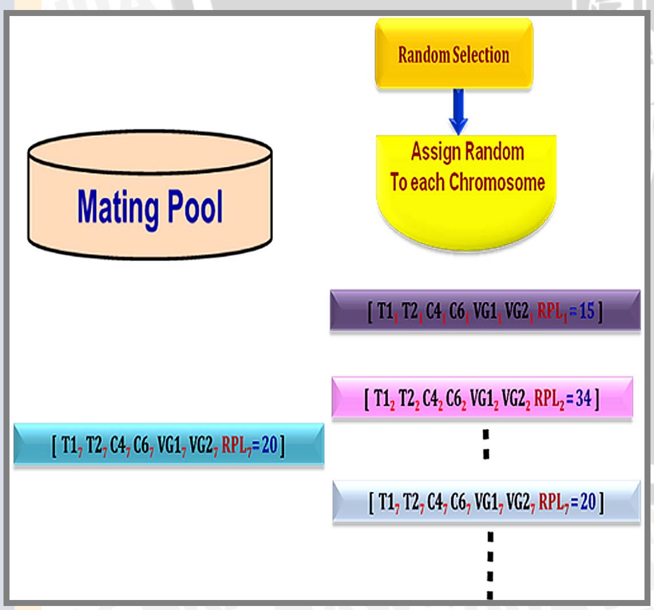

Fig 4: Random Selection Method Mechanism

b. Flat Crossover Technique

The offspring $H = (h_1,\ldots.h_i,\ldots.h_n)$ is generated in the Flat crossover randomly (uniformly) by randomly chosen a value for h_i from the interval (C^1_i , C^2_i).

c. Simple Crossover Technique

The offspring $H = (h_1,\ldots.h_i,\ldots.h_n)$ is generated in the Simple crossover by establishing a vertical crossover position then the two new chromosomes are built. Figure 6 will demonstrate this crossover mechanism.

C. MUTATION TECHNIQUES

Two GA mutations mechanisms will be presented in this section [4].

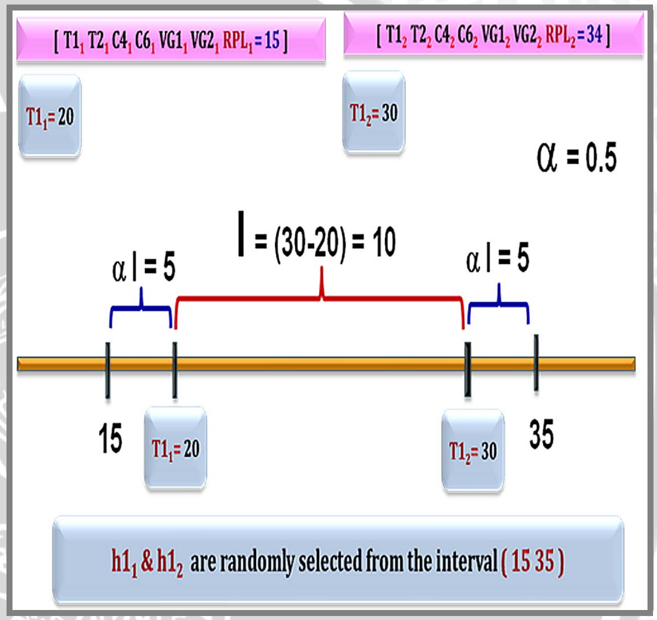

Fig.5: BLX Crossover Mechanism

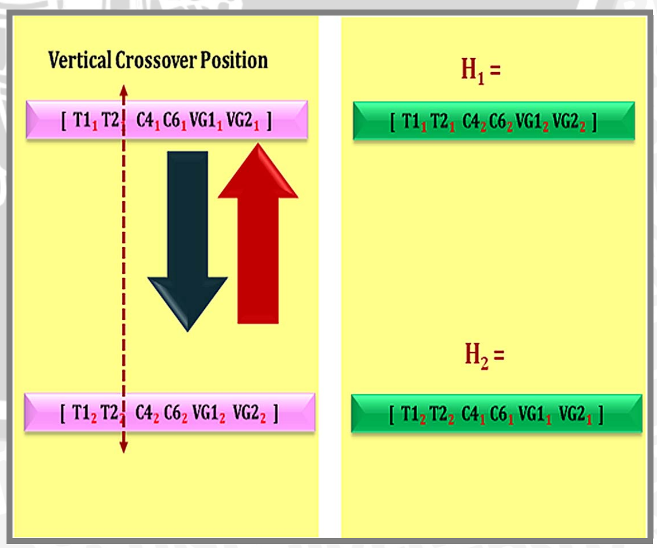

Fig.6: Simple Crossover Mechanism

a. Random Mutation Technique

In the random mutation method the new gene is generated randomly from the gene domain. For example the new h^1_1 gene is generated randomly from T^1_1 domain (T^{min} –T^{max} or 0.9-1.1).

b. Non-Uniform Mutation Technique

This method use the following equations for mutation

$$C'_i = \begin{cases} C_i + (b_i - C_i) * [1 - r^{(1-t/Gmax)^b}] & \text{when } \tau = 0 \\ C_i - (C_i - a_i) * [1 - r^{(1-t/Gmax)^b}] & \text{when } \tau = 1 \end{cases}$$

Given the followings;

1) τ is randomly generated number from the interval (0 1), when $\tau < 0.5$, then $\tau = 0$. If $\tau \geq 0.5$, then $\tau = 1$.
2) r is randomly generated number from the interval (0 1)
3) b is an integer number, b can be 5 or 3.
4) Gmax is the maximum number of Generations
5) t is the current Generation number.
6) a_i & b_i is the domain of the gene. For example in the T1 gene case $a_i = T^{min} = 0.9$ and $b_i = T^{max} = 1.1$.
7) C_i is the gene current value.

V. RESULTS AND DISCUSSION

In this section we will assess the optimal suggested variables **[T_1 T_2 C_4 C_6 Vg_1 Vg_2]** of the Wale & Hale 6 bus system in obtaining the minimum real power loss for different selection, crossover and mutation techniques. Moreover, a comparison of the convergent to the optimal (minimum real power loss) objective for these different GA techniques will be presented. In this assessment the initial population where set to 600 while the generation number was varied depends on the comparison as we will see in the coming sections.

A. Wale & Hale 6 Bus System

Wale & Hale 6 bus test system shown in Figure 1 was used in this paper. The simulation was carried out via the MATLAB Program with a single objective of minimizing the real power system in the system. This system variable is represented in a six genes chromosome as follows;

[T1 T2 C4 C6 Vg1 Vg2]

Where

T1 is the transformer between Bus#4 and Bus#3 tap setting
T2 is the transformer between Bus#6 and Bus#5 tap setting
C4 is Bus#4 shunt capacitor values in pu
C6 is Bus#6 shunt capacitor values in pu
Vg1 is Generator at Bus#1 voltage in pu
Vg2 is Generator at Bus#2 voltage in pu

The generator connected to bus#1 is the swing generator and the other generator connected to bus#2 is in Voltage-Control Mode with the specified MW generated power (50MW) and MVar limitation (-20MVar – 100 MVar). Bus#3 is load bus with 55MW real power and 13 MVar reactive power load, Bus#5 is a load bus with 30 MW real power and 18 MVar reactive power load, Bus#6 is load bus with 50MW real power and 5MVar reactive power load and also a nominated bus for hosting the shunt capacitor C6. Bus#4 is a nominated bus for hosting the shunt capacitor C4. Transformer T1 is the step down transformer between Bus#3 & Bus#4 (Bus#3 is the tap and high voltage bus), Transformer T2 is the step down transformer between Bus#5 & Bus#6 (Bus#5 is the tap and high voltage bus) [2,3].

B. Tournament Selection Method Vs Random Selection Method

To make this benchmarking a fair one similar crossover (BLX) method and mutation (Random) method were used. The maximum number of generation (Gmax=50) was also fixed.

Table 1: Tournament Vs Random Selection Comparison

	The Chromosome Genes Values						
Selection Method	T1	T2	C4	C6	Vg1	Vg2	Total Real Power Loss
Tournament	0.9553	0.9799	0.0537	0.0518	1.150	1.100	8.6981 MW
Random	0.9538	0.9874	0.0550	0.0550	1.150	1.100	8.6778 MW

The convergent assessment of these two GA selection techniques is demonstrated in Figure 7. Both converge at almost the same time, yet the random method has converged to better optimal value (real power losses).

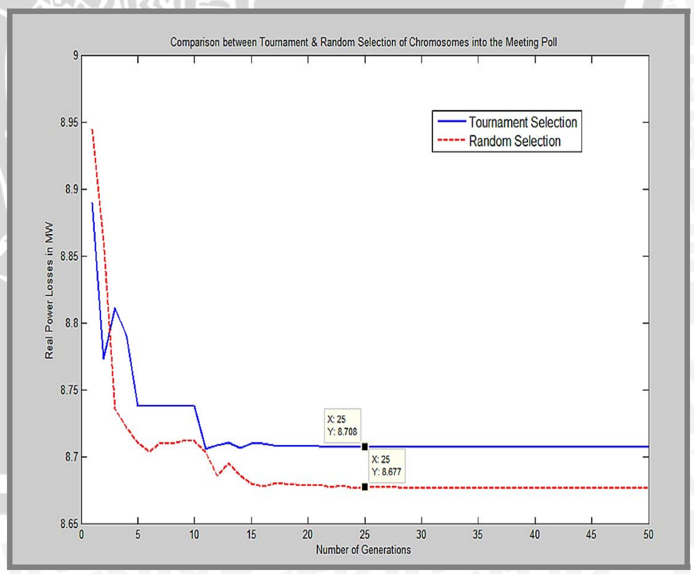

Fig.7: Objective Function Convergent for Different Selection Methods

C. BLX Crossover Method Vs Simple Crossover Method

To make this benchmarking a fair one similar selection method (random) and mutation (Non-Uniform) method were used. The maximum number of generation (Gmax=50) was also fixed.

D. BLX Crossover Method Vs Flat Crossover Method

To make this benchmarking a fair one similar selection method (random) and mutation (Non-Uniform) method were used. The maximum number of generation (Gmax=50) was also fixed.

In Figure 8 an evaluation of different crossover techniques in convergent to optimal objective is presented. In order to make this benchmarking a fair one, a similar selection method (random) and mutation (**Non-Uniform**) method were used. The maximum number of generation (Gmax=100) was also fixed. As per the below figure all the three (3) crossover method used with Non-Uniform mutation method did not converge after 100 generations.

Table 2: BLX Vs Simple and Flat Crossover Methods Comparison

Crossover Method	The Chromosome Genes Values						Total Real Power Loss
	T1	T2	C4	C6	Vg1	Vg2	
BLX	0.9530	1.0034	0.0538	0.0542	1.1500	1.1000	8.6960 MW
Simple	0.9632	0.9689	0.0536	0.0537	1.1500	1.0999	8.7018 MW
Flat	0.9655	0.9706	0.0530	0.0504	1.1493	1.0998	8.7274 MW

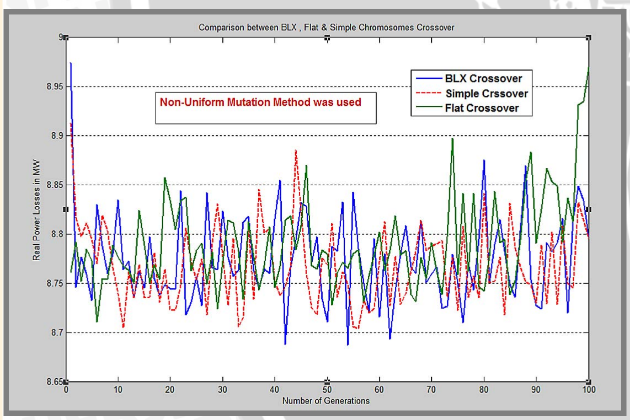

Fig. 8: Convergent for Different Crossover Method (Non-Uniform Mutation)

As in Figure 8 none of the crossover methods converge when the non-uniform mutation technique was used. So, we can conclude that this mutation technique is not a good choice for the reactive power optimization problem.
Another comparison using the random mutation technique is done between the different GA crossover techniques. Figure 9 where the maximum number of generation was set equal to 150 (Gmax=150) shows the convergent comparison for these three crossover methods. In this figure you can see that BLX and Simple crossover methods did converge when used with the random mutation method while the Flat crossover method did not converge. So, we can conclude that both BLX and the simple crossover method are suitable for reactive power optimization problem when used with random mutation technique.

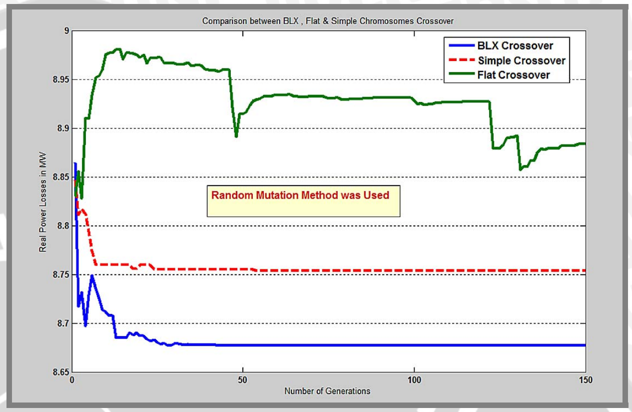

Fig. 9: Convergent for Different Crossover Method (**Random Mutation**)

E. Random Mutation Method Vs Non-Uniform Mutation Method

To make this benchmarking a fair one similar selection method (random) and crossover (BLX) method were used. The maximum number of generations (Gmax=50) was also fixed.

Table 3: Non-Uniform Vs Random Mutation Methods Comparison

Crossover Method	The Chromosome Genes Values						Total Real Power Loss
	T1	T2	C4	C6	Vg1	Vg2	
Non-Uniform	0.9530	1.0034	0.0538	0.0542	1.1500	1.1000	8.6960 MW
Random	0.9544	0.9867	0.0550	0.0550	1.1500	1.1000	8.6778 MW

VI. ANNUAL COST SAVING POTENTIAL

The annual cost saving potential between the optimal power system state and the initial state condition is summarized in the below table (Table 4). Using Wale & Hale 6 bus system and given the followings to obtain the optimal power state condition;

- Initial Population size of 600
- 50 Generations.
- Using Random selection.
- Applying BLX Crossover technique with 90% rate.
- Using Random Mutation with 10% rate.

There is a potential of saving around $600,000 annually comparing the initial system state condition to the optimal state conditions.

Table 4: Annual Cost Saving Potential

The Initial Power System State Condition					
T1	T2	C4	C6	Vg1	Vg2
1.0000	1.0000	0.000	0.000	1.0500	1.1000
Total Real Power Loss					**10.791 MW**
The Optimal Power System State Condition					
T1	T2	C4	C6	Vg1	Vg2
0.9548	0.9859	0.0550	0.0550	1.1500	1.1000
Total Real Power Loss					**8.677 MW**
The Potential Real Power Saving (PRPS)					**2.114 MW**
The Tariff per kWh					**0.032 $/KWh**
The Annual Potential Cost Saving (PRPS X Tarrif X 24 hrs X 365 days)					**592,596 $**

V. CONCLUSION

In this study the Genetic algorithm as global search optimization technique was implemented to minimize the real power system loss. This technique proved its capability to produce a very attractive optimization results and potential cost saving for Wale & Hale 6 bus system six (6) buses electrical power system. Any future studies need to be subject to the real life power system constrains, including the followings;

1) The transformer taps limitations; the real transformer taps is a step of ± 0.625% of the nominal voltage with total steps of ± 16 steps. So, the random selection of any value for the transformer taps between 0.9 – 1.1 of the nominal voltage need to be rounded to the nearest real life transformer tap.
2) The shunt capacitor standard size; the capacitor size needs to be subject to the market available standard sizes to avoid any sole capacitor size.
3) The technical difficulties of installing the capacitor in any of the proposed buses need to be part of the objective function for selecting the optimal power state condition.
4) The need for posting the generator bus voltage to its limit as a result of the optimal power state condition and the side effects of the same such as increasing the short circuit magnitude shall be thoroughly evaluated.
5) The possibility of using large synchronous motors in any system to be studied as a source of reactive power to reduce the need for larger shunt capacitors.

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